Pitfalls of In-Domain Uncertainty Estimation & Ensembling in Deep Learning

Arsenii Ashukha* Alexander Lyzhov* Dmitry Molchanov* Dmitry Vetrov



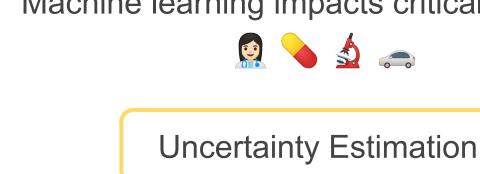








Machine learning impacts critical decisions





Reliable metrics





Wide comparison of existing techniques

Ensembles of DNNs

$$p_{\text{ens}}(y_i | x_i) = \frac{1}{K} \sum_{k=1}^{K} p(y_i | x_i, \omega_k)$$

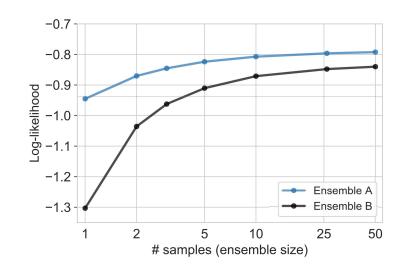
- Log-likelihood
- Brier score
- Calibration errors (e.g. ECE, TACE)
- Misclassification detection performance (AUCs)

The metrics can give a great method a low score

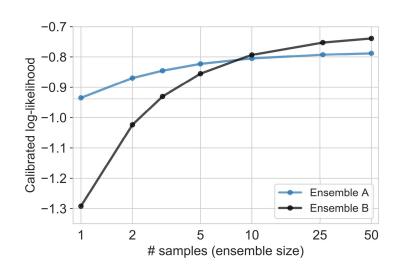
$$Log-likelihood = \sum_{(x,y)\in D} \log p_{ens}(y \mid x)$$

$$softmax(z)_i = \frac{exp(z_i/T)}{\sum_j exp(z_j/T)}$$

$$z \leftarrow \log p_{\text{ens}}(y \mid x)$$







Use calibrated log-likelihood instead of log-likelihood

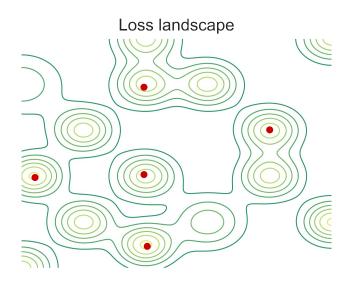
Brier score (like log-likelihood) needs calibration 🗸



- Calibration errors X
 - have model-specific biases
 - fail to provide consistent ranking depending on hyperparameters

Misclassification detection performance results in incompatible values for different models X

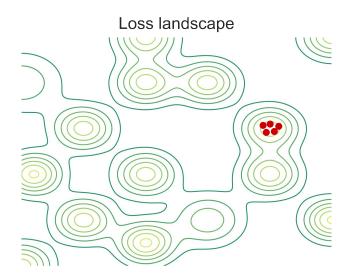
Ensembles of DNNs



Multimodal methods:

- Deep ensembles
- Snapshot ensembles
- Cyclical SGLD

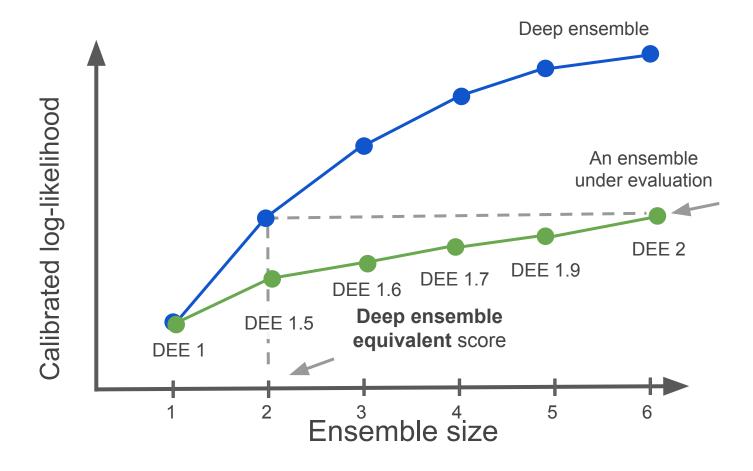
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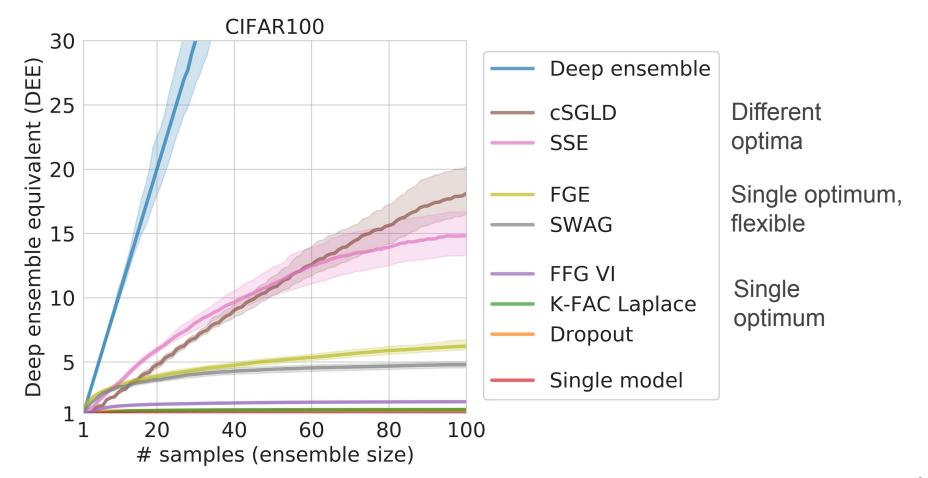
Local methods:

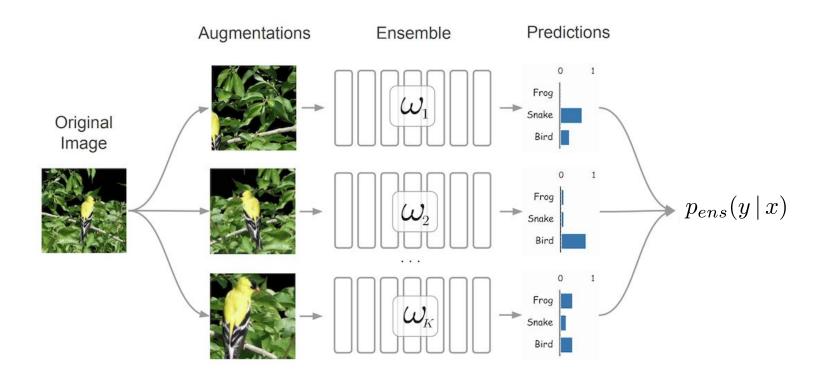
- MC-dropout
- Variational inference
- K-FAC Laplace
- Fast geometric ensembling
- SWA-Gaussian

- ...

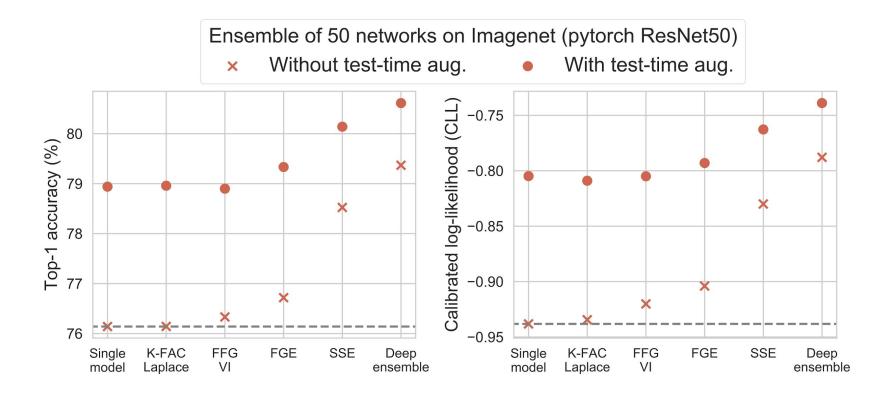


Deep ensemble equivalent score (DEE)





Test-time data-augmentation improves ensembles for free



Pitfalls of In-Domain Uncertainty Estimation & Ensembling in Deep Learning

- Metrics of in-domain uncertainty, e.g. log-likelihood, are unreliable, use *calibrated log-likelihood* instead
- Most ensembles are equivalent to a very small deep ensemble
- Test-time data augmentation improves ensembles for free



GitHub